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Predicting Possible Hydrologic Outcomes for Montane Meadow Ecosystems Following the 2012 - 2015 California Drought

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Abstract

Mountain meadows play a critical role in the hydrology of California's watersheds by preventing flooding, improving water quality, and delivering moisture downstream. In this study, the depth of the water table defines hydrologic health, where a shallow water table is considered a healthy hydrologic system. Meadows are highly sensitive to changes in water availability, making drought a particularly potent threat. This study investigated the health, vegetation distribution, and water balance of a montane meadow (Bluff Meadow) located in the San Bernardino National Forest. By integrating field observations of climate and water table depths in ArcGIS with hydrological modeling, this study assessed the health of the system, evaluated its sensitivity to regional precipitation, and modeled how this critical ecosystem may be irreversibly altered in an ever-warming world. The hydrologic model integrated the major variables of precipitation, surface temperature and humidity (model inputs) to predict the depth of the water table (model output) in both time and space. By calibrating the model against physical measurements of water table depth, predictions were made about the future hydrologic health (water table depth) of Bluff Meadow. Results showed that the drought had a dire effect on the future climate of California, which may be a permanent change. The hydrologic model gives best and worse case scenarios for Bluff Meadow as a result of the drought. If drought-like conditions continue, even with the El Nino this winter, the model predicts that the hydrologic health of the meadow will worsen over time. A recovery from this drought will take more precipitation than just one El Nino winter. Therefore, this study concluded that the 2012 – 2015 California drought was not just an instantaneous event, but a glimpse into California's future climate.

Introduction

An extraordinary drought spanned Southern California from 2012 – 2015, with 2014 being the driest year in the past century (Griffin and Anchukaitis, 2014; Swain et al., 2014). An extraordinary drought is one that lasts multiple years, with extremely high temperatures and extremely low precipitation (Woodhouse et al., 2010). In fact, California's total precipitation in 2014 fell within the bottom 6% of all of California's paleoclimatic records (Griffin and Anchukaitis, 2014). Not only was precipitation at an all time low during this drought, temperatures were also at a record high, which exacerbated the severity of the drought by about 36% (Griffin and Anchukaitis, 2014). This drought in particular was so extreme that it is labeled the most severe drought in California in the last 1200 years (Cook et al., 2004; Griffin and Anchukaitis, 2014; Woodhouse et al., 2010). While high temperatures are likely an anthropogenic effect of global warming, the cause for decreasing precipitation is undetermined (Mann et al., 1998; Swain et al., 2014). If global warming is the cause of this increased dryness, then many parts of the United States can expect a dry future (Cook et al., 2004; Seager et al., 2007). California's drought began in 2012 and continues through 2016, with below average precipitation relative to the 1895-2015 mean (Figure 1).

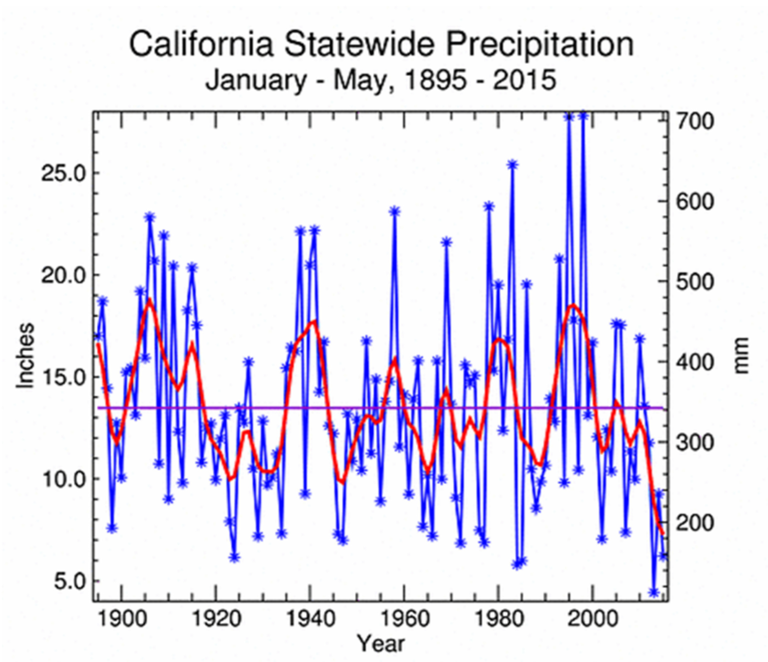


Figure 1. Annual precipitation for California over the 1895 – 2015 time period. A 5-year running mean is plotted in red (NOAA).

The extremity of the recent drought was not unprecedented, meaning it is not the first time such a severe drought has occurred in climatic history (Cook et al., 2004; Cook et al., 2007; Griffin and Anchukaitis, 2014; Woodhouse et al., 2010). Paleoclimatic data suggests that even longer and more severe periods of elevated temperature and aridity have occurred in North America in the past, especially during the mid-12th century when repetitions of decadal droughts persisted (Cook et al., 2014; Woodhouse et al., 2010). During this Medieval Warm Period, average temperatures in the Southwestern United States rose by 1°C and aridity increased due to high irradiance levels of 0.45 W/m^2 (Woodhouse et al., 2010). Some studies propose that the combination of long-term warming and aridity during the 2012 – 2015 drought compares it to the mid-12th century drought, which may serve as an analog for what the climate could look like in the future (Woodhouse et al., 2010). This probability is likely, given that 44% of three-year droughts last for at least four years, which suggests that California may have to adjust to this warm, dry climate (Ault et al., 2013; Griffin and Anchukaitis, 2014). A "megadrought" has not occurred since the foundation of modern society, but is still a possibility given their occurrence in the climatic past (Ault et al., 2013). With such severity and duration, these multi-decadal droughts brutally impact the agricultural and hydrologic systems of their affected areas (Cook et al., 2007). Because California is a water dependent state, a "megadrought" would be catastrophic for the state's environment and society. Given the significant impact that a drought could have both agriculturally and economically, a state implemented risk management plan suggests the development of mitigation plans in preparation for the future climate (Christian-Smith et al., 2014). These mitigation plans need to consider all indicators that the climate of California is changing, not just the historic patterns of drought, but also climatic forces.

The El Nino Southern Oscillation (ENSO) is often invoked as a strong climatic force that controls wet and dry conditions in California. Described as a weakening of trade winds across the equatorial Pacific, El Nino is associated with above average sea surface temperatures. While El Nino's are generally correlated to a wet season for California, La Nina's suggest a dry season and are associated with below average sea surface temperatures in the eastern equatorial Pacific. The ENSO phenomenon operates on interannual timescales, with an El Nino occurring every 2-7 years (Schonher and Nicholson, 1989). However, climatic forces that operate on decadal time scales also contribute to California's climate. The Pacific Decadal Oscillation (PDO) was discovered in 1996 and has been described as a long-lived version of the ENSO pattern, oscillating between warm and cool phases every 20-30 years. During the warm phase of the PDO, the equatorial Pacific is warm, while the Northern Pacific is anomalously cool, favoring El Nino-like conditions. The reverse is true during the cool phase, where a cool equatorial Pacific and warm Northern Pacific favor La Nina-like conditions. The PDO oscillated between the warm and cool phases several times over the past century (Figure 2). Although the warm phase persisted from 1980-2010, this tendency is declining and the climatic pattern suggests that the trend is heading into a cool phase for the next 20-30 years. This cool phase is associated with La Nina-like conditions in the equatorial Pacific. While El Nino produces more precipitation and lower temperatures in California, La Nina generates a dry and hot climate. The flip-flop from the warm to cool phase of the PDO predicts that California is going to become much drier as the climate enters the La Nina period (Mantua and Hare, 2002). The patterns of severe droughts and historical trends in ENSO and the PDO indicate that California should be prepared for more than just an anomalous dry spell. Climatic variability shows that the future climate of California is going to mimic the symptoms of an ongoing drought. Because of the dire effects that a drier climate would have on California's hydrologic system, its society needs to prepare for the possibility of an ever-warming world (Seager et al., 2007; Woodhouse et al., 2010).

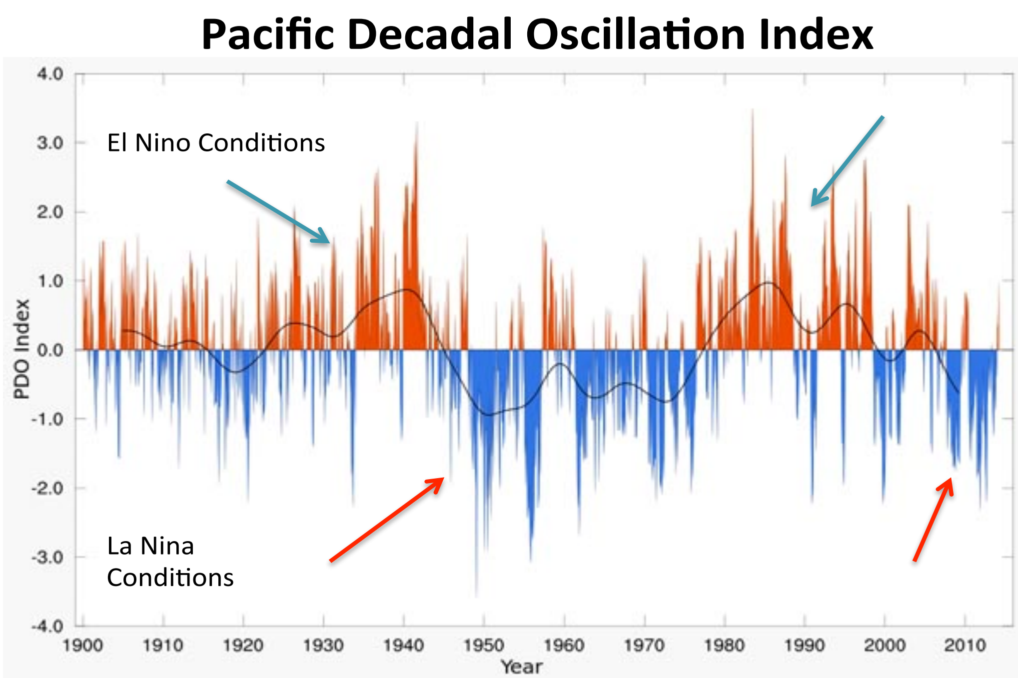


Figure 2. The Pacific Decadal Oscillation (PDO) from 1900 – 2015. Warm phases (red) of the PDO are associated with El Nino-like conditions while cool phases (blue) are associated with La Nina-like conditions.

A drier climate depletes groundwater, increasing the depth to the water table, changing soil thickness and making it more difficult for plants to hydrate from their roots. These consequences can lead to the loss of groundwater dependent vegetation in the ecosystem (Debinski et al., 2010; Kotanen, 1997; Loheide and Gorelick, 2007; Lowry and Loheide, 2010; Orellana et al., 2012). This loss of vegetation typically occurs when the groundwater reaches depths of 2-5 meters below the surface, which is lower than the average plant root depth in montane meadow ecosystems (Elmore et al., 2006). Many cases of vegetation loss have been reported in the Sierra Nevada mountain region of California due to changes in climate (Allen, 1987; Guarín and Taylor, 2005; Null et al., 2010). Because droughts and possible future dry climates could majorly impact the state's water resources and agriculture, being able to measure and quantify the intensity of the recent California drought would be beneficial in predicting the expected changes in California's ecosystems. A great place to measure these hydrologic changes is in montane meadows.

Meadows are very important, yet fragile features of mountain ecosystems (Allen, 1987; Benedict, 1982; Ratliff, 1985). When it rains on the mountain, the water travels downstream to the flat meadow, which soaks up this moisture into its permeable soil and slows runoff speeds. This sponge-like quality is the cause for meadows' shallow water tables, which is what makes them so vital to mountain ecosystems (Ratliff, 1985). The water is then naturally filtered through the ground, which prevents floods, and delivers moisture downstream by way of groundwater. All in all, montane meadows have a major impact on California's hydrologic system by preventing flooding, improving water quality, and delivering moisture downstream (Null et al., 2010). Each of these qualities is extremely sensitive to small changes in climatic variables, especially decreases in water levels, as would be expected in a drought (Essaid et al., 2014; Lowry et al. 2011). The depth from the surface to the water table underground determines these changes in water levels. A shallower water table indicates healthier vegetation, and the stability of a meadow ecosystem is dependent on the health of its vegetation (Benedict, 1982). If California is to lose meadow ecosystems to a dry climate, mountains would no longer benefit from the qualities that meadows offer. Therefore, a drier climate would predict a loss of vegetation, increased flooding and decreased groundwater recharge downstream, creating a negative feedback loop for many ecosystems outside of the meadow. The sensitivity of meadow ecosystems to changes in water availability and the short time scales over which they operate make them ideal for measuring the effects of drought.

This study investigated the effects of precipitation, water flow, temperature, humidity, irradiance, and incision on a mountain meadow ecosystem by measuring the changes in depth from the surface to the water table. The water table is the depth underground at which unsaturated soil ends and saturated soil, or groundwater, begins. A summer water table is lower than a winter water table due to decreases in precipitation and increases in temperature (Figure 3). In this study, changes in these climatic variables were measured and related to changes in water table depth, which fluctuates in the zone of intermittent saturation (Figure 3).

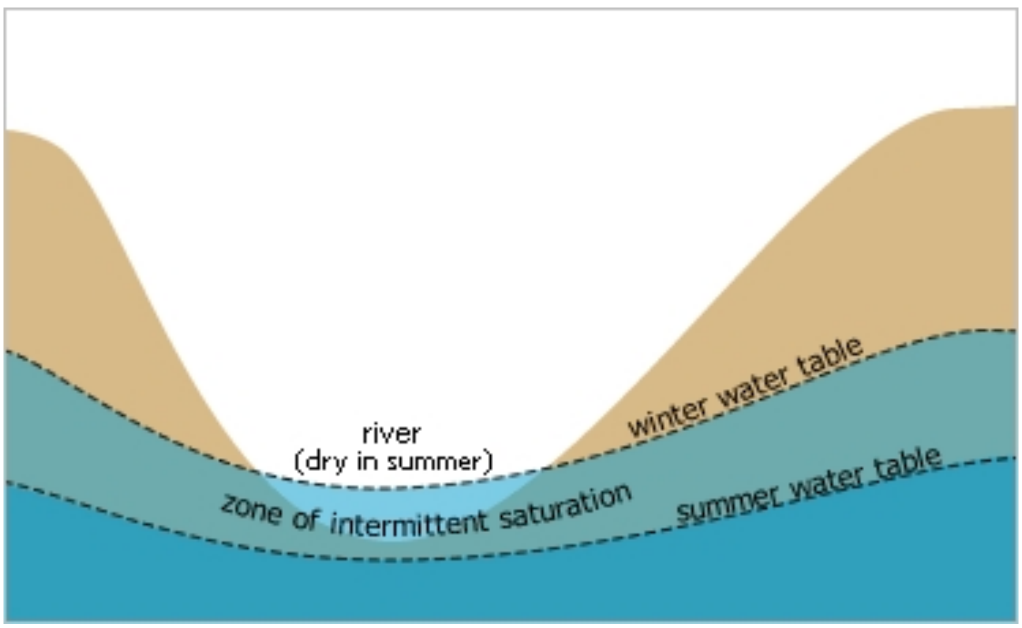


Figure 3. The water table is the surface of the groundwater beneath the land. The depth to the water table changes based on season due to changes in precipitation and temperature levels. Adapted from http://www.birdsoutsidemywindow.org/2011/08/22/the-water-table/

Because California has many montane meadows, the relationship between vegetation type and depth to the water table has previously been compared and modeled in healthy, incised, and restored conditions in Sierra Nevada mountain meadows (Essaid et al., 2014; Loheide and Gorelick, 2007; Lowry et al., 2011; Wood, 1975). Findings show that groundwater dependent ecosystems are most vulnerable to stream incision and climate change, which both result in the lowering of the water table. Having the ability to predict future changes in climate would help determine expected vegetative responses (Loheide and Gorelick, 2007; Lowry et al., 2011). While many studies have been done in the Sierra Nevada's, very little research has been done in the San Bernardino's. To examine the effects of drought-like conditions on the ecosystem and model possible cases for the future, this study analyzed an incised meadow (Bluff Meadow) in the San Bernardino Mountains, where the water table was deeper than average.

During the summer of 2015, well instruments were installed in Bluff Meadow to measure changes in water table depth (American Rivers, 2012). Twelve wells were distributed throughout the meadow to track groundwater availability spatially, calculate changes in groundwater levels temporally, and ultimately create a hydrologic model of this data. Once the data was modeled, the climatic factors that had the most impact on the health of the meadow were confirmed. The model predicts groundwater levels over time based on changes in the region's temperature and precipitation, the two most influential climatic factors on water table depth. With the model's computations, changes in hydrologic parameters such as precipitation, temperature, humidity, and irradiance create an accurate prediction of hydrological results for the ecosystem. The purpose of this research was to generate an overall forecast for the future hydrologic health of California. The results compare outcomes to historical data patterns, make predictions for the future, and observe how different future cases could affect the ecosystem.

Field Methodology

Field Site

The original field site for this project was Big Meadows, a montane meadow in the San Bernardino National Forest, located ten miles southwest of Big Bear Lake in Big Bear, California. Unfortunately, the Lake Fire in the San Bernardino Mountains began on June 18, 2015, the day before the first intended fieldwork day, and took the meadow with it. This led to a two-week search for a new field site and delay in data collection. The new field site was Bluff Meadow, also a montane meadow in the San Bernardino's, located two miles south of

Big Bear Lake in Big Bear, California (Figure 4). Bluff Meadow is 300 meters in length, 7.5 acres in area, and 2300 meters in elevation. The meadow is much browner and drier on the eastern half and much greener and wetter on the western half (Figure 4).

Figure 4. The research team during a data collection day in Bluff Meadow, Big Bear, CA (location in California shown by map in bottom right corner). This photo is taken from the western side of the meadow, facing east. The change from healthy to dry vegetation is apparent, as one looks eastward.

The extreme difference in vegetative health from one end of the meadow to the other could be explained by the incision in the main stream that runs through the meadow on its northern border. When a stream becomes incised, or V-shaped, narrow, and deep, it forces the water table to drop in the land surrounding the stream. This is one of the most prominent reasons for the loss of montane meadow ecosystems, and is a common feature observed during a time of water deprivation, such as a drought (Loheide and Gorelick, 2007; Lowry et al., 2011). The eastern half of the stream in Bluff Meadow is extremely incised, which explains the dry vegetation corresponding to that side of the meadow. With these vegetative observations, the water table is expected to be much deeper on the eastern, incised, dry side of the meadow than the western, non-incised, wet side of the meadow.

Well Installations

To measure changes in depth to the water table, it was important to reach the meadow's groundwater noninvasively. The method used in this study involved installing small wells made out of PVC pipe (Figure 5). Water entered each well through holes drilled into the bottom of the pipe, and soil was kept out by wire mesh glued to the inside of the pipe (American Rivers, 2012).

Figure 5. An example of a completed well made of PVC pipe, ready for installment in the meadow. Adapted from http://www.solinst.com/products/direct-push-equipment/615-drive-point-piezometers/datasheet/standpipe-piezometers.php

In Bluff Meadow, twelve installment sites were selected for these wells at varying location, topography, and vegetation (Figure 6). At each chosen installment site, narrow, deep holes were dug until the water table was reached. The average depth of each hole was about two meters. The wells made of PVC pipe (Figure 5) were then inserted into the holes, their tops were capped to avoid contamination, and the remaining space was filled with soil.

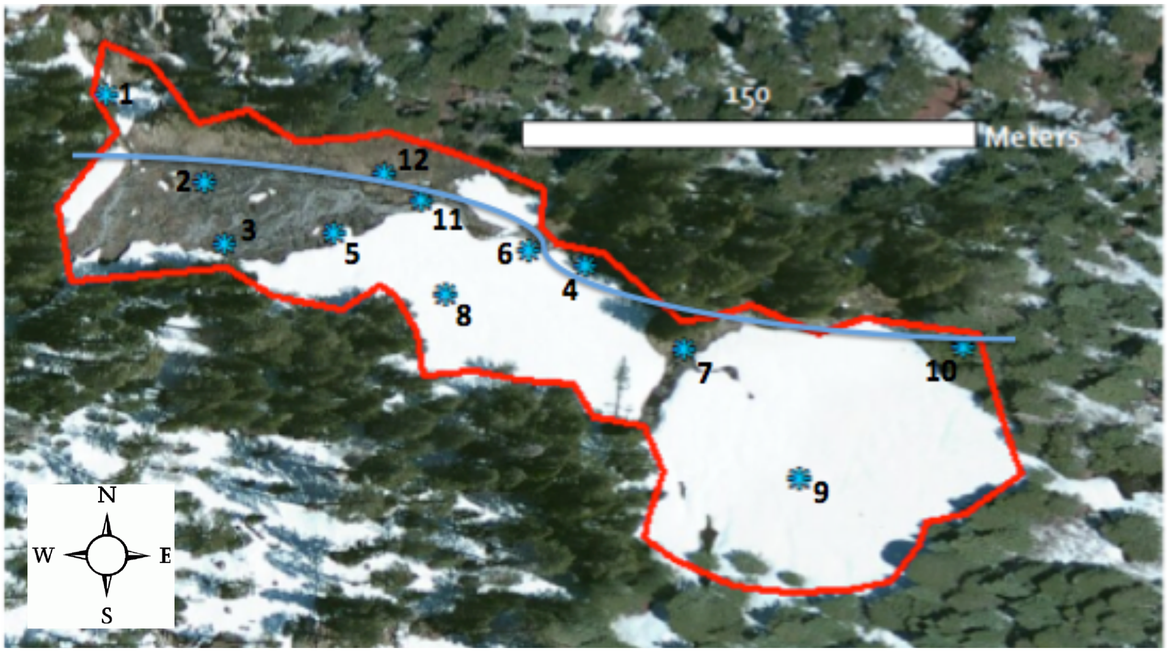


Figure 6. Blue asterisks depict locations of the 12 wells in Bluff Meadow, whose area is bounded by the red border. The blue line displays the stream that flows through the north side of the meadow.

The depth to the water table was measured at each well with a water level meter (Figure 7). A water level meter is essentially a long cord with a sensor on the end that beeps when it touches water. The cord was dropped into the well and lowered until a beep sounded. The cord was marked at the height of the PVC pipe and then pulled out of the well to measure the length of cord from mark to sensor (Figure 8). The height of the PVC pipe sticking out of the ground was then subtracted from the total length of the cord it took to reach the water, purely giving the depth to the water table.

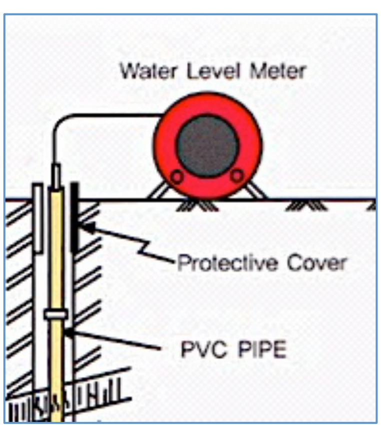


Figure 7. The water level meter, used to measure the depth to the water table.

Figure 8. The depth to the water table is measured with the water level meter by measuring the length of cord that it took to reach the water table.

Observational Results

Water Table Depths

Water table depths at each of the twelve wells in Bluff Meadow were measured weekly from July to October in 2015. These measurements were averaged over three week periods and are displayed in *Table 1*. The red values indicate wells that dried out during the months of data collection and were labeled as "dry wells". Since the water table at these "dry wells" had lowered beneath the depth of the well, the water table depth at these "dry wells" were recorded as the depth of their well. Note that wells 4, 6, 7, 9, 10, 11, and 12 were all considered dry wells at some point over these four months.

Table 1. Weekly water table depths (mm) were averaged over sets of three weeks during observational data collection (July – Oct 2015). A red value indicates a dry well, where the water table depth was recorded as the depth of the well.

Water Table Depths (mm)

Well	Jul 2 - Jul 22	Jul 23 - Aug 12	Aug 13 - Sep 9	Sep 10 - Oct 1	Oct 2 – Oct 23
1	148.17	177.80	402.17	287.87	389.47
2	251.88	234.95	650.66	353.48	328.08
3	194.73	76.20	859.37	325.97	224.37
4	374.65	1384.30	1384.30	1384.30	1384.30
5	711.20	558.80	935.57	673.10	728.13
6	660.40	1028.70	1295.40	1295.40	1295.40
7	740.83	901.70	1341.97	1765.30	1765.30
8	351.37	406.40	660.40	457.20	427.57
9	1765.30	1765.30	1765.30	1765.30	1765.30
10	1765.30	1765.30	1765.30	1765.30	1765.30
11	222.25	444.50	982.13	1295.40	1295.40
12	831.85	1104.90	1295.40	1295.40	1295.40

Climatic Data

During the observational period, temperature, humidity, precipitation, and irradiance (radiation from the sun) were measured. Temperature and humidity were measured weekly at the surface of each well, using an Xplorer GLX device. Annual average monthly temperature and precipitation data for the Big Bear region was taken from the U.S. climate data website and averaged over the last four years (Figure 9). Notice that during these four years, there was a correlation between increases in temperature and decreases in precipitation, which shows the expected seasonality in a year. Average monthly humidity data was taken from NOAA and irradiance data was taken from Sengupta et al. (2014). Using temperature and humidity data, Bluff Meadow's evapotranspiration rates were calculated. Evapotranspiration is the combination of evaporation off of the land and transpiration off of plants, both of which are a loss of water from the system.

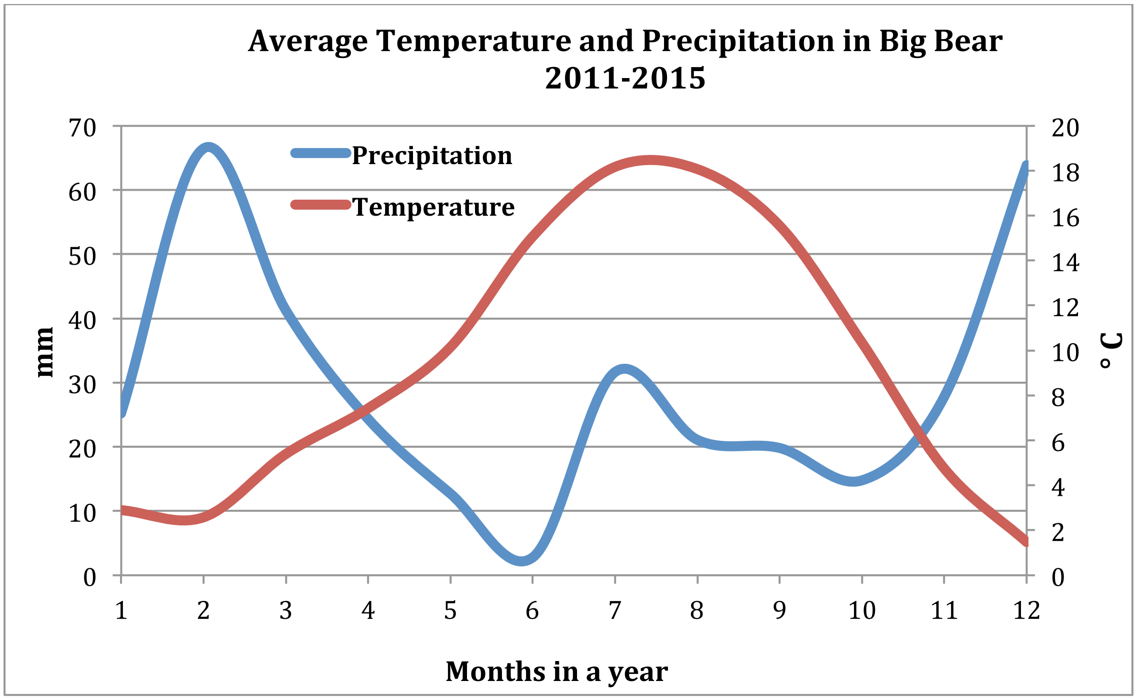


Figure 9. Monthly temperature and precipitation in the Big Bear region, averaged monthly from 2011 to 2015.

Spatial Data

Water table depth, temperature, and humidity data were entered into an ArcGIS mapping system to observe the spatial changes over the twelve wells in Bluff Meadow through time. The point data collected from each well was interpolated, or connected over space, in ArcGIS to determine the data values between the twelve individual data points. Contour maps of each climatic variable over the span of the entire meadow were created with the interpolation tool in ArcMap.

Water Table Depths

With interpolation, water table depths between the twelve discrete measured data points were observed. *Figures 10* and *11* are examples of interpolations of the water table displayed in contour maps from the weeks of July 6th and July 28th. Red represents a deep water table (> 2.2 meters) while green represents a shallow water table (< 0.3 meters). The water table deepens over the month of July. This deepening occurs on the northern border of the meadow, where the stream is located (as seen in Figure 6). The concentration of deepening on the northern border is most likely due to the deepening of the incision in the stream, which in turn deepens the water table. The water table on the eastern side of the meadow was much deeper than the western side, which is due to the deeper incision on the eastern side, and would be expected from the initial vegetative observations (Figure 4).

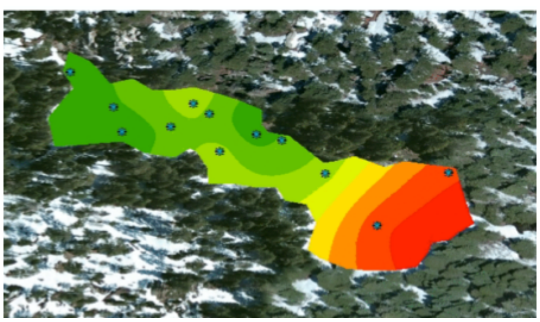
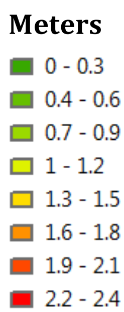


Figure 10. Water table depth (m) interpolation from July 6th



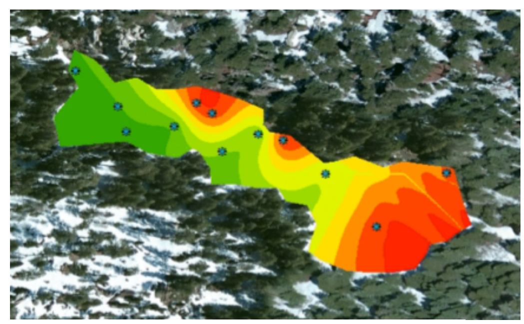


Figure 11. Water table depth (m) interpolation from July 28th

Temperature

With interpolation, temperature between the twelve discrete measured data points were observed. *Figures 12* and *13* are examples of interpolating temperature, displayed in contour maps from the weeks of July 6th and July 28th. Red represents a warm temperature (> 42°C), while blue represents a cool temperature (< 23°C). Temperatures were somewhat consistent during the month of July. If anything, the warm spots and cool spots shift westward, possibly from differing angles of the sun during these two data collection days. Shifts in temperature over the wells were bound to change the interpolation layout of humidity over the meadow.

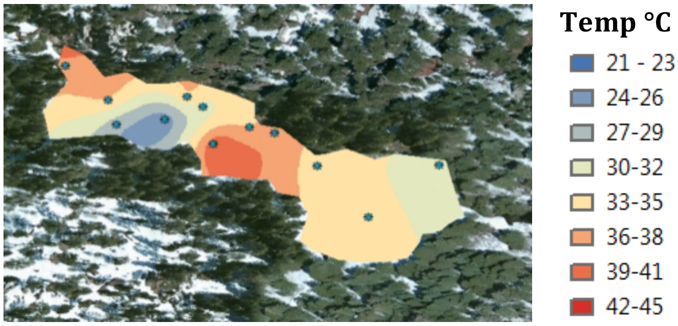


Figure 12. Temperature (°C) interpolation from July 6th

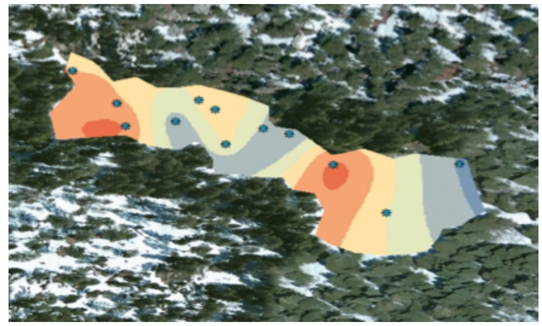


Figure 13. Temperature (°C) interpolation from July 28th

Humidity

With interpolation, humidity between the twelve discrete measured data points were observed. *Figures 14* and *15* are examples of interpolating humidity in contour maps from the weeks of July 6th and July 28th. Dark blue represents high humidity (> 41%), while light blue represents low humidity (< 15%). Humidity decreased during the month of July. July 6th was much more humid, with the edges of the meadow being the most humid. The spots of dark blue were locations where it tended to be shadier. On July 28th, it was the most humid on the northern border, where the stream was located (as seen in Figure 6). The center of the meadow, where the sun hit, was quite dry. There was somewhat of a correlation between temperature and humidity. Warmer locations (Figure 12 and 13) were associated with less humid locations (Figure 14 and 15) and vice versa.

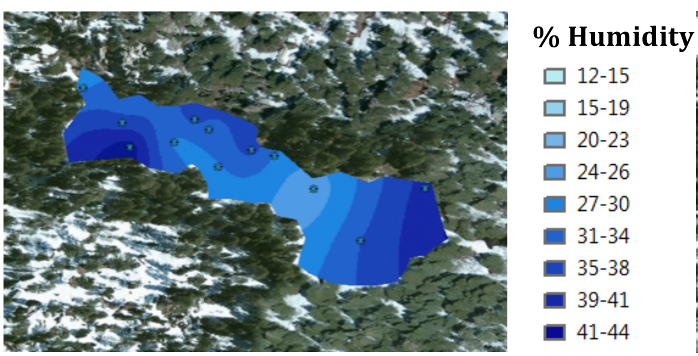


Figure 14. Humidity (%) interpolation from July 6th

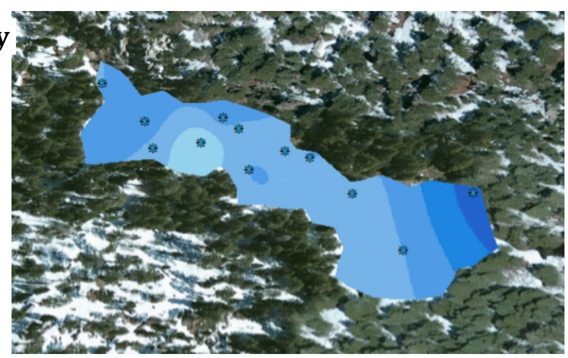


Figure 15. Humidity (%) interpolation from July 28th

Hydrologic Model

To predict the future hydrologic health of Bluff Meadow, it was essential to predict the future climatic variables that the hydrologic health depended on first. The predictions of climatic variables were calculated with real climatic data inputs from previous years in order to output accurate, realistic results. The model input was a predicted climatic case based on patterns from previous years and the model output was predicted water table depths.

Temperature Prediction

Future monthly temperatures over each well were predicted by

$$\frac{T_{i_{measured}}}{T_{i-1_{measured}}} = \frac{T_{i_{predicted}}}{T_{i-1_{predicted}}}, \tag{1}$$

where *T* represents temperature and *i* represents a chosen month. This calculation equated the ratio of measured temperatures to predicted temperatures. Measured temperatures came from observational monthly temperature data, taken from U.S. Climate Data. The measured temperature that was input mimicked the climatic patterns of that month. For example, if 2017 was modeled as a dry year, 2013's measured temperature data was used as the input because it was a very dry year. *Equation 1*'s relationship suggests that the ratio between measured temperatures of month *i* and month *i-1* remains constant for future consecutive months. This equation assumes that the pattern of temperature change from one month to the next increases or decreases by the same proportion every year. This relationship solved for predicted temperatures in month *i*, used that value to predict month *i+1*, and repeated to predict temperatures into future years. To start this cycle of monthly relationships, the first input for predicted temperature was the observed temperature from July 2015. With July 2015 as a starting point, temperatures were projected into future months and years based on the type of climatic patterns intended to imitate.

Evapotranspiration Prediction

Evapotranspiration was calculated with the arid version of the Turc equation (1961), given by

$$ET = 0.013 \times \left[\frac{T}{T+15}\right] \times (R + 50) \times \left[1 + \frac{50-H}{70}\right] \tag{2}$$

where T stands for temperature, R stands for irradiance, and H stands for relative humidity (Dyer, 2015; Trajković et al., 2007). The arid version of this equation was used because average relative humidity is less than 50% in Southern California, making humidity an independent variable and factoring it into the hydrologic model (Dyer, 2015). Evapotranspiration plays a key role in water table depth because it is the main source of water loss during a dry season in an incised ecosystem (Essaid et al., 2014). *Equation 2* was also used to calculate predicted evapotranspiration, which was the same calculation used to find real time evapotranspiration. However, instead of entering real time temperature into the equation for T, the predicted temperature (T_{pred} calculated in *Equation 1*) was entered for the month that evapotranspiration was being predicted. Neither irradiance nor humidity were predicted because the data used for those inputs were annual monthly averages, and were therefore expected to stay constant over time.

Water Table Prediction

A Water Balance Equation gives the total water storage in a system by subtracting the variables leaving the system by the variables entering the system. In this study, the storage was groundwater, the inputs were precipitation (P) and stream water inflow, and the outputs were evapotranspiration (ET) and stream water outflow. However, the drought caused the stream to dry up, so there was no stream water inflow or stream water outflow in this study's Water Balance Equation. Therefore, the change in water table depth was

$$\Delta WT = P - ET, \tag{3}$$

where real time precipitation and evapotranspiration data were input and real time changes in water table depth were output. To predict a future change in water table depth, the Difference Equation was used, which was

$$\Delta WT = WT_{i-1} - WT_i, \quad (4)$$

where the change in water table was defined as it's initial value minus it's final value, to indicate a drop in water table as a negative change. To predict into the future, the Water Balance Equation (Equation 3) was set equal to the Difference Equation (Equation 4), and WT_i, was solved for which gave

$$WT_i = WT_{i-1} - (P - ET_{pred})_i. \quad (5)$$

This was the equation that the model used to predict water table depths into the future, with measured water table depths from the previous month, measured precipitation data from a chosen year, and predicted evapotranspiration data derived in *Equation 2*.

Verification of Model

To prove that the hydrologic model was valid and could be used to make accurate predictions for the future of California, the predicted climatic variables and a future prediction trial case were tested and verified.

Predicted Temperature

Data collection took place for four months, from July to October 2015. The predicted temperatures that the model calculated based on July 2015's measured temperature patterns were compared to the measured temperatures from August through October to verify that the model predicted temperature patterns accurately. First, the measured and predicted temperature data were normalized. The difference (predicted – measured) between each well's average measured and average predicted temperatures from the months of August-October were calculated at each of the twelve wells (Figure 16). The model over-predicted temperature in wells 1-5 and 7-8 and under-predicted temperature in wells 6 and 9-12. This made sense because when referring to *Table 1*, wells 4, 6 and 9-12 were the driest wells throughout data collection. Since their temperatures were under-predicted, the actual temperatures present at each well were higher than expected; therefore, the wells were drier than predicted. Well 4 was slightly over-predicted by the model, so its inclusion in the "dry" wells was valid. During data collection, wells 1-3, 5 and 8 were consistently wet, corresponding to their over-predictions in temperature. Since they were expected to be hotter than they actually were, they were wetter than predicted.

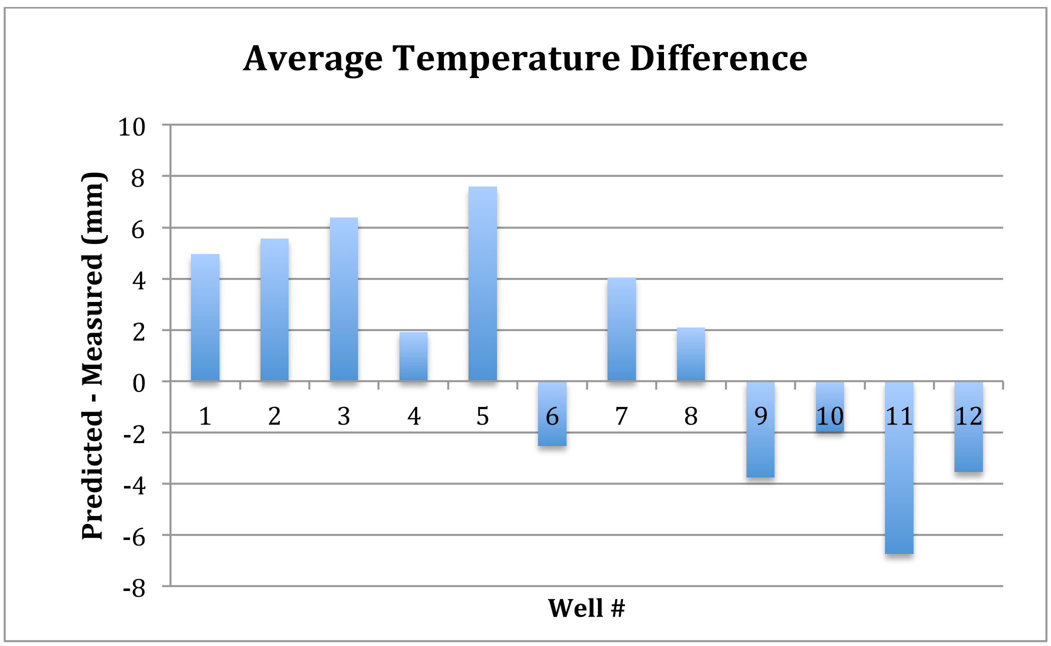


Figure 16. The difference between normalized average predicted and measured temperatures from August to October 2015 determined accuracy of temperature predictions. A positive bar represents an over-prediction while a negative bar represents an under-prediction.

The relationship between measured and predicted temperature was linear, as evidenced by the regression correlation coefficient and the linear fit of the data (Figure 17). The linear fit gave a correlation of r = 0.681, further verifying that the temperature predictions calculated by the model were accurate.

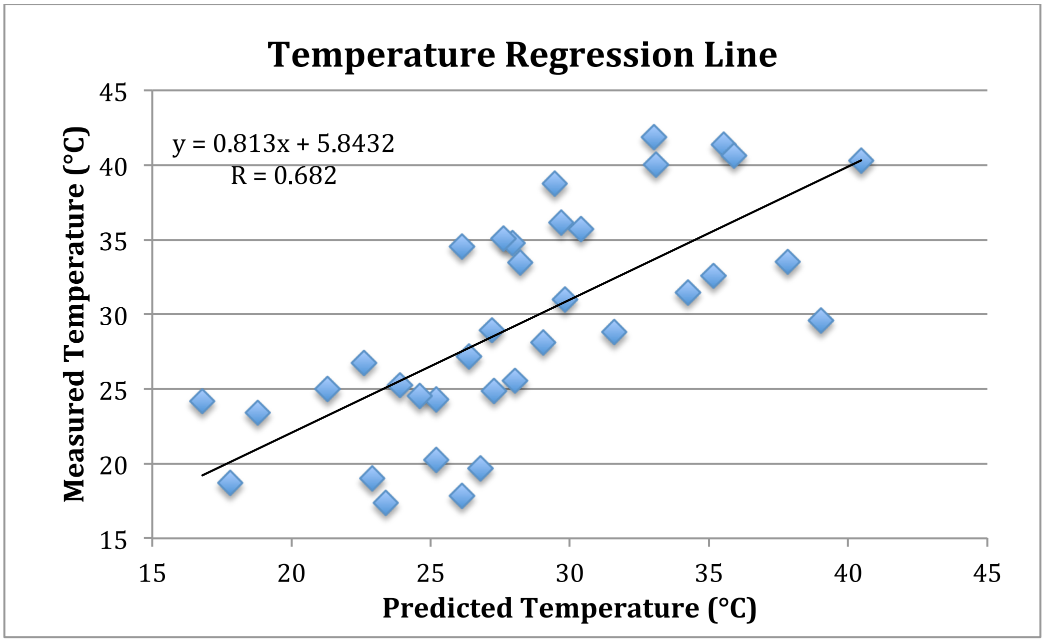


Figure 17. Regression line of measured temperature versus predicted temperature gave an r-value of 0.682, indicating a strong relationship between measurements and predictions.

Predicted Water Table

The measured and predicted water table data from August to October was also normalized. The difference (predicted – measured) between each well's average measured and average predicted water table depths were calculated at each of the twelve wells (Figure 18). The model over-predicted the water table depths in wells 9 and 10, and under-predicted water table depths in wells 1-8 and 11-12. An over-prediction meant that the model hypothesized that the well would be drier than the resulting measurement concluded. A small over-prediction of wells 9 and 10 made sense because they were the absolute driest wells throughout data collection, never having any water in them at all. The hypothesized prediction was that their wells would be very dry and their water tables would be very deep. Since their water table depths were over-predicted, the measured water table depth present at each well was shallower than expected; therefore, the wells were wetter than predicted. The rest of the wells were under-predicted, meaning their measured water table depths were deeper than their predicted depths. An under-prediction meant that the model hypothesized that the well would be wetter than the resulting measurement concluded. Wells 6, 7, 11, and 12 were very under-predicted, so, the measured water table depth present at each well was deeper than expected; therefore, the wells were drier than expected. This extreme under-prediction made sense because these four wells were in close proximity to the incised stream in the meadow, and would therefore be the first to dry up when the stream became waterless.

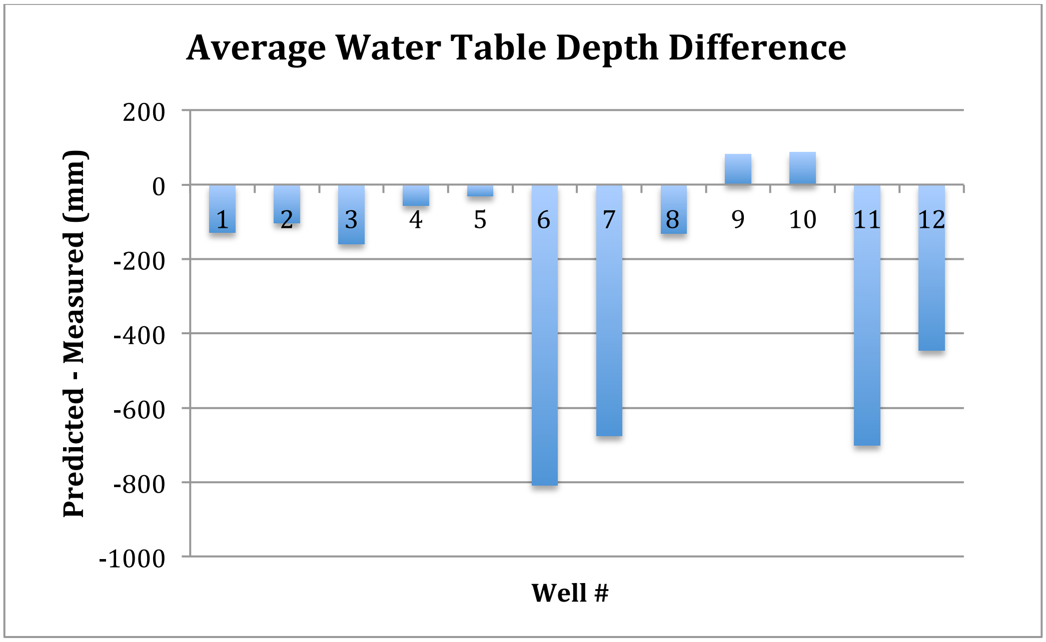


Figure 18. The difference between normalized average predicted and measured water table depths from August to October 2015 determined the accuracy of water table depth predictions. A positive bar represents an over-prediction while a negative bar represents an under-prediction.

The relationship between measured and predicted water table depths were linear, as evidenced by the regression correlation coefficient and the linear fit of the data (Figure 19). The linear fit resulted in a correlation of r = 0.642, further verifying that the water table depth predictions calculated by the model were accurate.

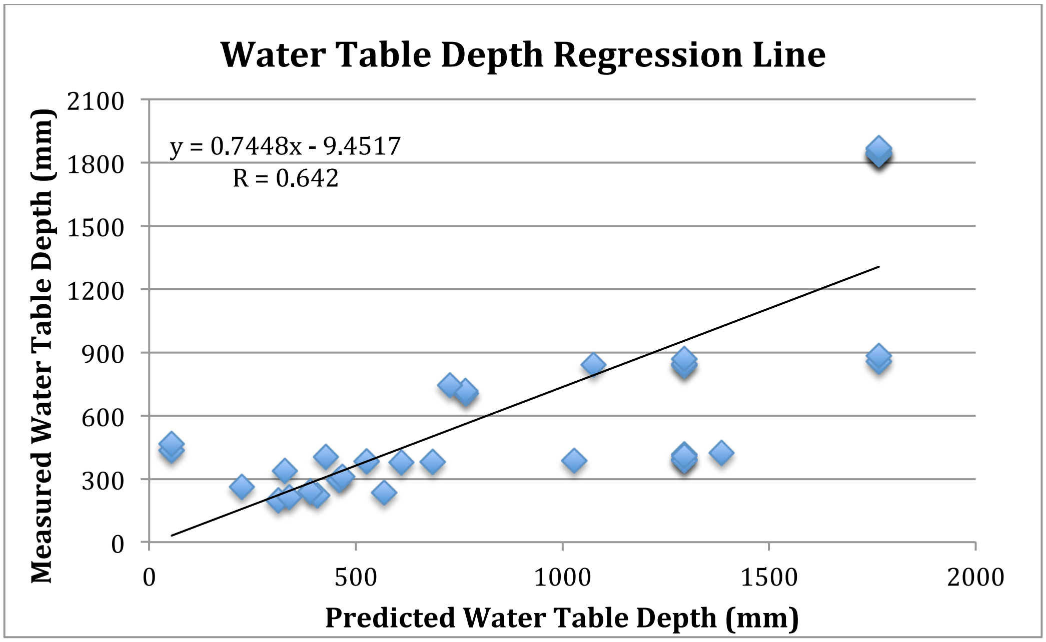


Figure 19. Regression line of measured water table depths versus predicted water table depths gave an r-value of 0.642, indicating a strong relationship between measurements and predictions.

The hydrologic model accurately predicted data spatially by plotting measured and predicted water table depths over the twelve wells in Bluff Meadow (Figure 20). The model accurately predicted the pattern of the water table over the meadow in comparison to the actual pattern of the measured water table. For the most part, the model predicted that the water table was shallower than the measured data results. This means that the model gave the drought in Bluff Meadow the benefit of the doubt by predicting a slightly shallower water table than the deep water tables observed in the meadow. This positive outlook played a key role in predicting the drought's impact in future years to come because it suggests that the model's predictions are less extreme than the real consequences of this drought.

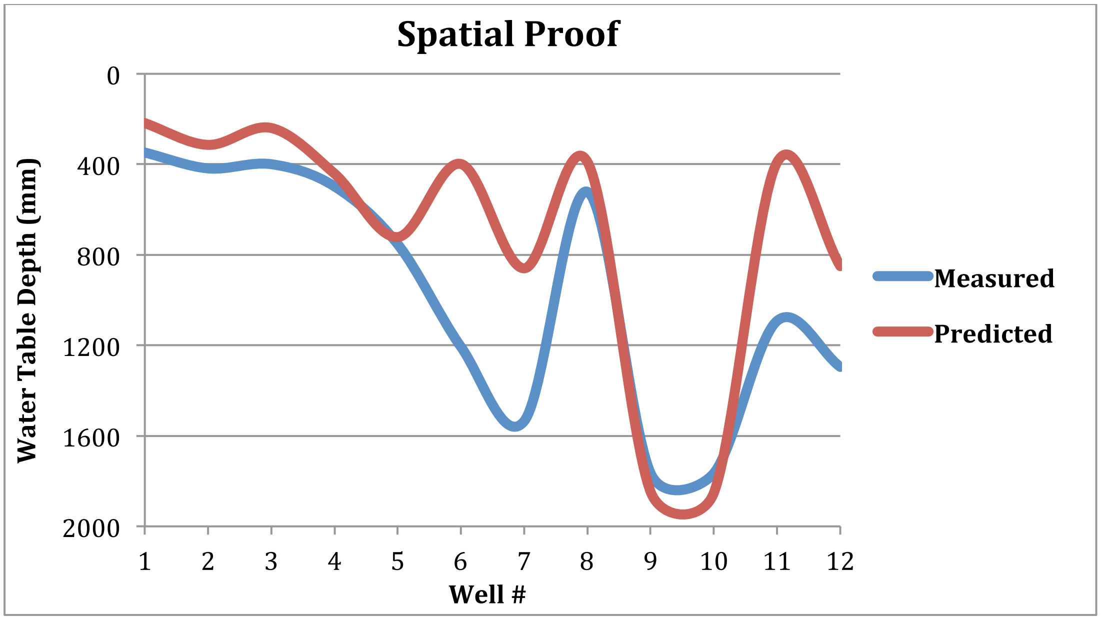


Figure 20. Measured and predicted water table depths over the 12 wells during the months of August to October were plotted against each other to verify that the model predicted the spatial patterns of the water table in Bluff Meadow accurately.

The hydrologic model accurately predicted data temporally by plotting average monthly measured and predicted water table depths (Figure 21). This temporal proof shows that over time, the model followed the correct pattern of changes in water table depth, but that it actually under-predicted the severity of the deepening water table. Because it followed the correct pattern, but the values were slightly inaccurate over a month-to-month time scale, it was assumed that the model would make predictions more accurately over a year-to-year time scale. The temporal proof results also inferred that the predictions the model made were less severe than what is expected in the future, just as the spatial proof showed.

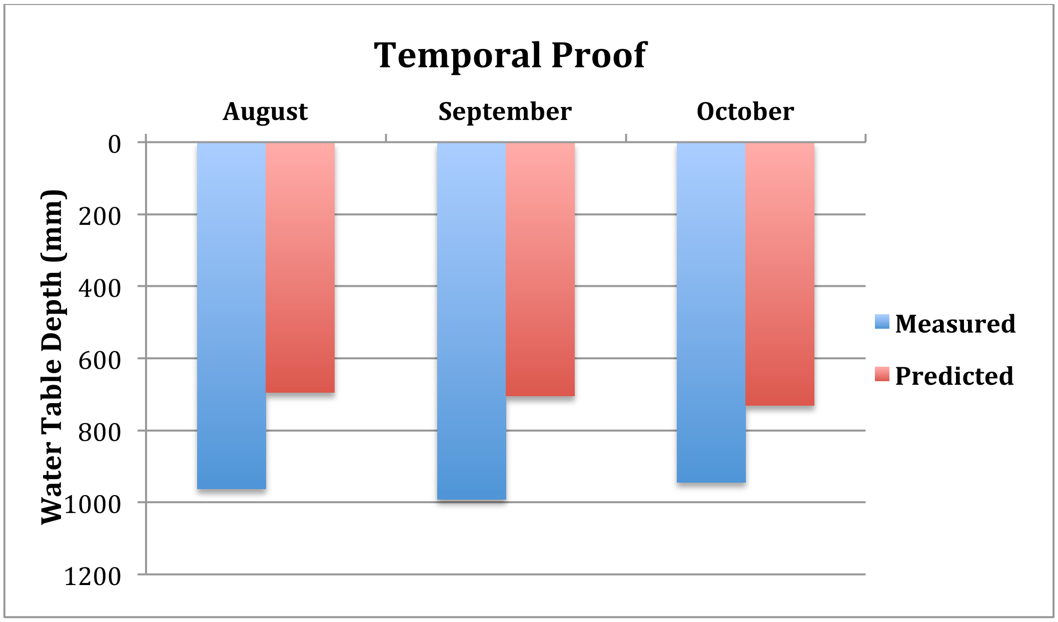


Figure 21. Measured and predicted water table depths were averaged from the months of August to October and plotted against each other to verify that the model predicted the temporal patterns of the water table in Bluff Meadow accurately.

The model predicted future water table depths in Bluff Meadow with the water table depth prediction (Equation 5). Another experiment was designed to verify the validity of the model by predicting an El Nino for the winter of 2015 before it happened, then seeing how well the model predicted the El Nino once it occurred. In October 2015, the measured data from July to October 2015 was entered into the model to make a prediction for future water table depths following a predicted El Nino in the winter of 2015. The model used 1997 – 1998's climatic data to predict an El Nino in 2015 – 2016 because it was a big El Nino winter. Climatic data from 2014 was used as the input for 2017 and onward, assuming that future years would be like 2014, which had a significantly wet winter in the Big Bear region. The prediction showed that the El Nino would help raise the water table in the spring of 2016, after the precipitation from the wet winter (Figure 22). Once the El Nino ended, and the 2014 climatic patterns began, the water table deepened. The model predicted that by 2019, the water table would be twice as deep as that of 2015. These results show that one El Nino winter will not save California. It may help replenish water resources in 2016, but if another El Nino does not occur in the next couple of years, water deprivation may get worse.

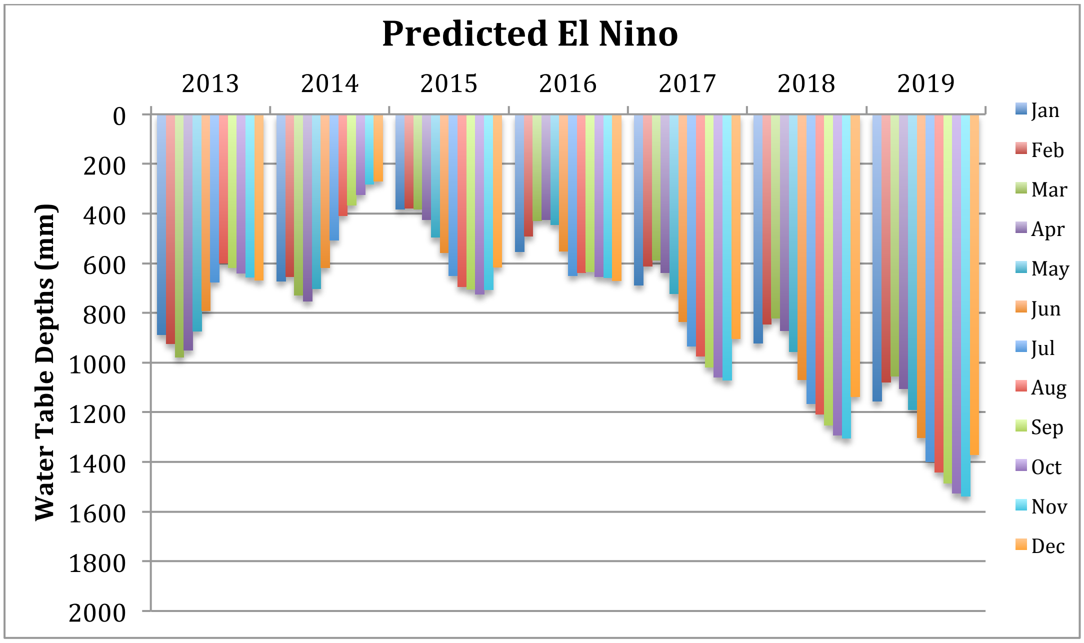


Figure 22. The hydrologic model predicts future water table depths of Bluff Meadow assuming an El Nino winter in 2015. Real climatic data was used for 2013 – 2014, 1997 data was used for 2015, 1998 data was used for 2016, and 2014 data was used for 2017 – 2019.

This El Nino prediction, produced in October 2015, was then compared to the actual El Nino winter results, produced in February 2016 (Figure 23). It was the same prediction as *Figure 22*, but real climatic data was used for 2015, instead of assuming that the data would be similar to that of 1997. The prediction results from these two cases were very similar, meanjng that the model did a good job of predicting water table depths into the future. These predictions were also credible in that they portrayed the seasonality of each year. The winters of each year had shallower water tables, as expected with it being a rainy season, while the summers had much deeper water tables, as expected with very little precipitation during those months. The accurate comparison between the prediction of 2015's El Nino winter and its actual results conclusively verified that the model could be used to predict into future years.

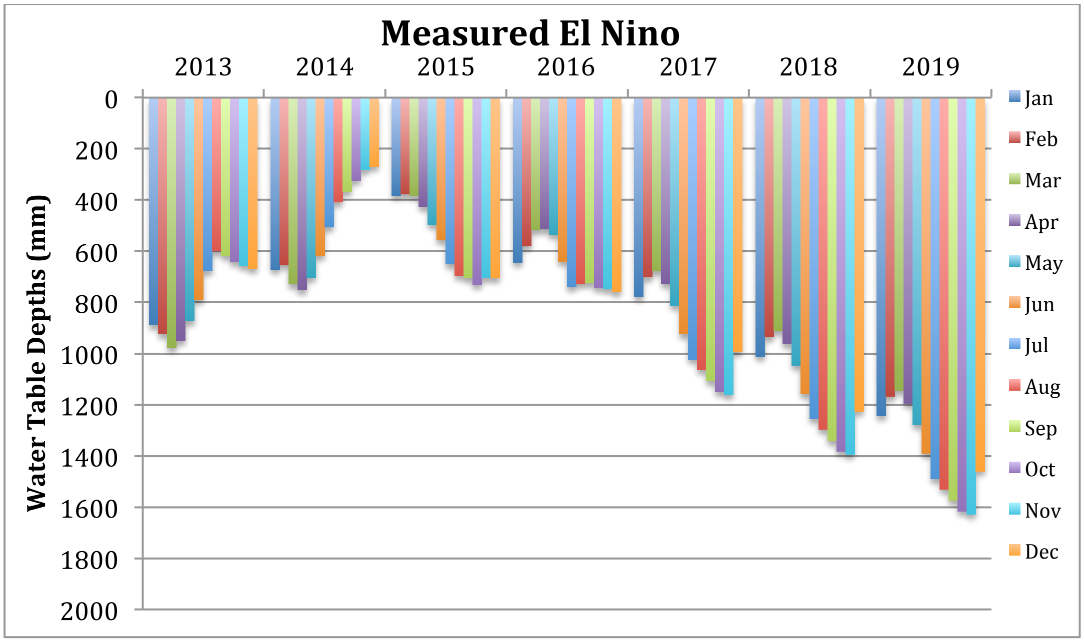


Figure 23. The hydrologic model predicts future water table depths of Bluff Meadow with the real data from an El Nino winter in 2015. Real climatic data was used for 2013 – 2015, 1998 data was used for 2016, and 2014 data was used for 2017 – 2019.

Model Results

The verification of the model showed that it predicted water table depths into the future accurately, and therefore could be used to predict into future years.

Three cases are presented for the future of the meadow:

1) Worst Case Scenario
2) Best Case Scenario
3) Changing Climate Scenario

Worst Case Scenario

In the worst-case scenario, temperatures were predicted to be higher than average and precipitation to be lower than average (Figure 24). The combination of these extremes was expected to create a drought-like scenario, which would result in a deepening of the water table. Climatic data during 2016 – 2019 was assumed to be similar to climatic patterns in 2012, the driest year in Big Bear during the drought. A consecutive hot and dry climate over the next four years showed a decline in the water table (Figure 24). This prediction showed that the water table would deepen dramatically each year, with 2019's water table depths (2200 mm) tripling the water table depths measured in 2015 (700 mm) (Figure 24).

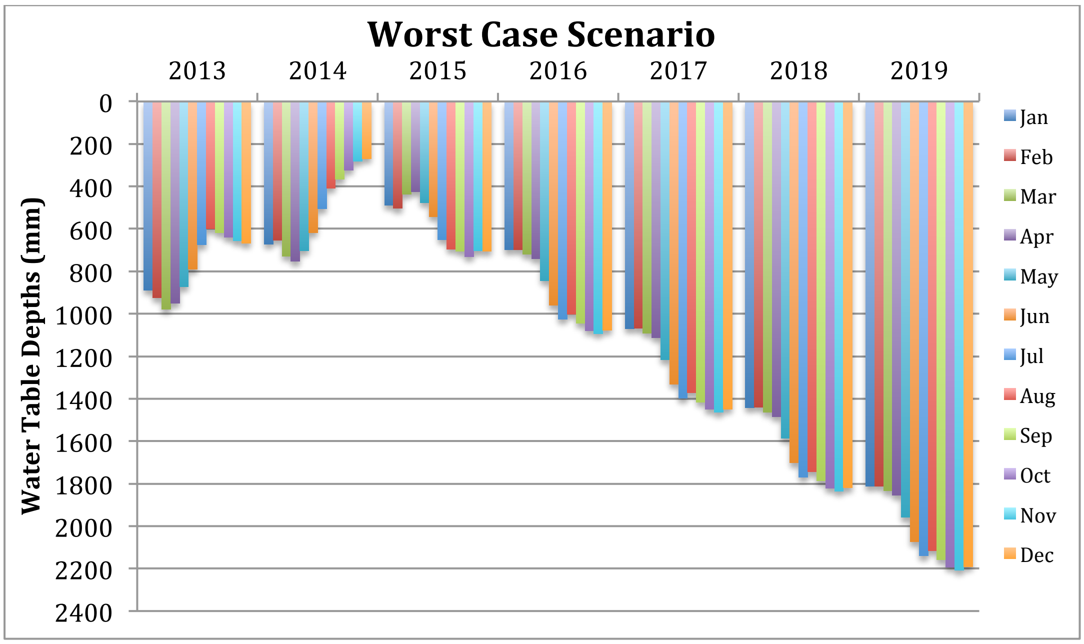


Figure 24. The hydrologic model predicted future water table depths of Bluff Meadow in a worst-case scenario. Real climatic data was used for 2013 – 2015 and 2012's climatic data was used for 2016 – 2019 because 2012 was the driest year of the drought in the Big Bear area.

Best Case Scenario

In the best-case scenario, temperatures were expected to be below average and precipitation to be above average (Figure 25). These trends are usually seen during El Nino winters. Therefore, 1998's climatic data was used as the input for years 2016 – 2019, since the winter of 1997 – 1998 was the one of the largest El Nino's seen in recent history. In this scenario, mild temperatures and abundant precipitation cause evapotranspiration rates to decrease and water table depths to rise closer to the surface (Figure 25). In 2019, water table depths (900 mm) were less than half the depth observed in the worst-case scenario (2200 mm). While the water table depths appeared to stay almost constant over the next four years, water table depths would be expected to rise to the surface of the meadow once the ecosystem recovered from the 2012 – 2015 drought.

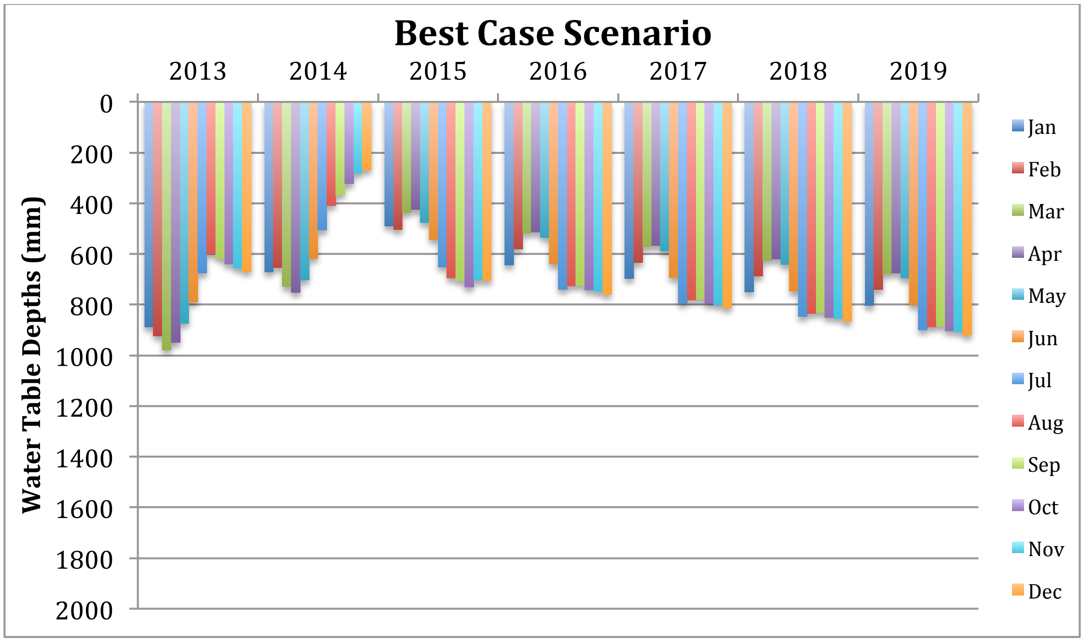


Figure 25. The hydrologic model predicted future water table depths of Bluff Meadow in a best-case scenario. Real climatic data was used for 2013 – 2015 and 1998's climatic data was used for 2016 – 2019 to predict an El Nino winter amount of precipitation for the next 4 years.

Changing Climate Scenario

A changing climate scenario would not be as extreme as the best or worst case scenarios, but somewhere in between (Figure 26). This case assumes that California's climate patterns will become hotter and drier, and that droughts are expected to become more common. The climatic data from the 2011 – 2015 recent drought was averaged and used as the climatic data for future years. This assumed that the next four years will have less dramatic climatic patterns than those seen in the worst-case scenario (Figure 24*)* but less positive than those seen in the best-case scenario (Figure 25*)*. Rather, a constant mild drought for the near future was predicted, showing a deepening water table with time, but not quite as dramatically as in the worst-case scenario (Figure 26). By 2019, the model predicted that water table depths would drop down to 1800 mm, double the depths in the best-case scenario (900 mm). This changing climate case portrays a future that many expect to see in California. As the climate heads into more favorable La Nina-like conditions in the Pacific, the norm is anticipated to become warmer temperatures and scarcer precipitation, resulting in something similar to this prediction.

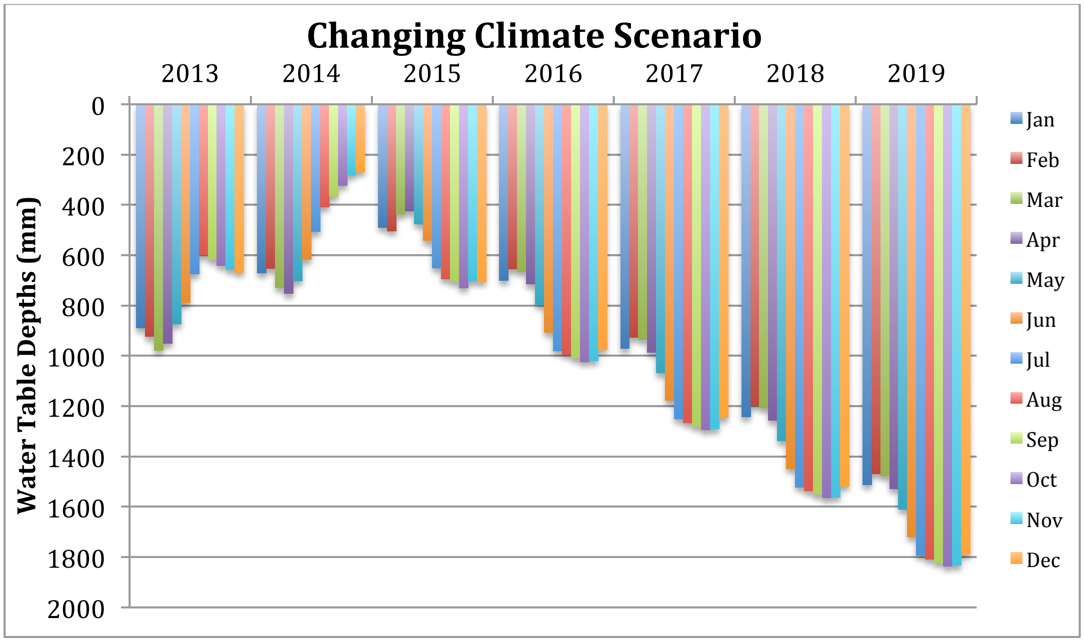


Figure 26. The hydrologic model predicted that the climate was changing and that mild droughts were going to become the norm in California. The climatic data used for the predicted years was taken from the averages of real data from 2011 – 2015, the years of the most recent drought.

Conclusion

While anthropogenic effects aggravate climate change on a global scale, local conditions in California appear particularly susceptible. Paleoclimatic drought patterns and climate forces, such as the El Nino Southern Oscillations and the Pacific Decadal Oscillation, predict that the climate of California is entering a dry and warm trend (La Nina). It is theorized that the 2012 – 2015 drought was not an instantaneous event, but the new climatic norm for the state of California. This change in climate would have dire effects on the state's vegetative and hydrologic health. Because meadow ecosystems are very sensitive to small changes in climate, Bluff Meadow in the San Bernardino Mountains was chosen as a field site to measure the effects of the 2012 – 2015 California drought on the ecosystem. Montane meadows are very important to a mountain's ecosystem because they act as a sponge for the precipitation that falls onto the mountain, absorbing runoff and distributing it through groundwater downstream. The drought's impact on the ecosystem was quantified by the change in groundwater levels, or the depth to the water table over time. The depth to the water table was measured from July – October 2015 with twelve well instruments, installed throughout the meadow. The depth to the water table was found to be dependent on temperature, precipitation, humidity, and irradiance. Based on observational data from Bluff Meadow, a hydrologic model was built to predict water table depths into the future, given different climatic scenarios. The computation, accuracy, and seasonality of the model was tested and verified both spatially and temporally to prove that it could make realistic predictions for the future. The model predicted three different scenarios for California over the next four years – a best-case scenario with wet winters (El Nino), a worst-case scenario with a continuous drought, and a changing climate scenario with warming and drying conditions (La Nina). The worst-case scenario predicted that the depth to the water table in 2019 would be triple that of 2015. The best-case scenario predicted that the depth to the water table would stay about constant until 2019. The changing climate scenario predicted that the depth to the water table would increase, but not to the extremity of the worst-case scenario. Because the climate is expected to enter a La Nina trend, the case that the future of California is most likely to mimic is the changing climate scenario. The prediction for Bluff Meadow made by the model serves as a predictive analog for the entire hydrologic system of California. Groundwater levels are expected to deepen as the climate becomes warmer and drier, forecasting the losses of riparian vegetation, groundwater recharge, and meadows. The loss of these groundwater dependent systems could fundamentally alter California's climate and ecosystem. Possible consequences of this climate change may be the economic collapse of agriculture, the ultimate depletion of groundwater, and the widespread occurrence of mudslides and flooding at mountain bases. These past climatic patterns and future hydrologic predictions demonstrate that California may be stepping out of an unusually wet period of atmospheric history and into an unknown, dry, and ever-warming world.

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